

Comparing Local Analysis and Prediction System (LAPS) Assimilations with Observations

Christopher A. Hiemstra*¹

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Glen E. Liston¹

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Roger A. Pielke, Sr.¹

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Daniel L. Birkenheuer²

¹Department of Atmospheric Science, Colorado State University, Fort Collins, CO 80523-1371

²NOAA Forecast Systems Laboratory, Boulder, Colorado 80305-3328

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Corresponding Author:

*Christopher A. Hiemstra, Ph.D.

Department of Atmospheric Science, Colorado State University

1371 Campus Delivery, Fort Collins, Colorado 80523-1371

hiemstra@atmos.colostate.edu

PH: (970) 491-3647 FAX: (970) 491-3314

ABSTRACT

Meteorological forcing data are necessary to drive many of the spatial models used to simulate atmospheric, biological, and hydrological processes. Unfortunately, many areas lack sufficient meteorological data and available point observations are not always suitable or reliable for landscape or regional applications. NOAA's local analysis prediction system, LAPS, is a meteorological assimilation tool that employs available observations (meteorological networks, radar, satellite, soundings, and aircraft) to generate a spatially distributed, three-dimensional, representation of atmospheric features and processes. As with any diagnostic representation, it is important to ascertain how LAPS outputs deviate from a variety of independent observations at different spatial and temporal scales. Fortunately, a number of observations exist that are not used in the LAPS system, and they were employed to assess LAPS performance during two consecutive years (1 September 2001-31 August 2003). LAPS assimilations were remarkably accurate in depicting temperature and relative humidity values temporally and spatially. The ability of LAPS to represent wind speed was satisfactory overall, but accuracy declined with increasing elevation. Lastly, precipitation estimates performed by LAPS were irregular and reflected inherent difficulties in measuring precipitation.

1. Introduction

Meteorological forcing data are necessary to drive many of the spatial models used to simulate atmospheric (Liston et al. 1998; Westrick et al. 2002), ecosystem (Parton et al. 1998; Running et al. 1988; Scuderi et al. 1993), and hydrological processes (Jasper et al. 2002; Liston et al. 2002). Unfortunately, many areas (e.g., high elevation mountains, intermountain shrublands, deserts) lack meteorological data. Furthermore, available point observations are not always suitable for landscape or regional applications (Pielke et al. 2002), especially in forested and mountainous regions.

The National Oceanic and Atmospheric Administration's local analysis prediction system (LAPS, <http://laps.fsl.noaa.gov/>) is a meteorological data assimilation tool that employs a suite of observations (meteorological networks, radar, satellite, soundings, and aircraft) to generate a realistic, spatially distributed, time-evolving, three-dimensional representation of atmospheric features and processes (Albers et al. 1996). Data produced by LAPS include wind speed, wind direction, surface temperature, relative humidity, surface pressure, precipitation, and cloud cover. Because LAPS is a spatially distributed representation of meteorological observations, it provides important opportunities for users who require local (10 or finer horizontal grid increment) meteorological data to drive distributed land surface and ecosystem models over large regions. The intention of LAPS is not only to provide an up-to-date atmospheric state representation for nowcasting and assessment, but it can also serve as a mechanism to initialize local-scale mesoscale weather forecast models.

As with any diagnostic representation, it is important to ascertain how LAPS outputs deviate from a variety of observations at different spatial and temporal scales. Since many readily available observations (e.g., National Weather Service, various state-level departments of transportation, FAA weather) are integrated into LAPS, they cannot be used to assess diagnostic

performance. Fortunately, a number of observations are not used in LAPS. Our objective was to employ independent meteorological data sources to examine relationships among LAPS assimilations and observed data with respect to meteorological variables commonly used as terrestrial model drivers: temperature, relative humidity, wind speed, and precipitation.

a. Study area

The 1,312,500 km² LAPS domain encompasses the states of Colorado, Wyoming, and portions of South Dakota, Nebraska, Kansas, Oklahoma, New Mexico, Arizona, Utah, Idaho, and Montana of the United States (Fig. 1). The weather, topography, and land cover of the domain are typical of the Great Plains (Sims et al. 2000) and Rocky Mountain (Peet 2000) regions. The weather is continental and dry with relatively high summer and cold winter temperatures. The landforms shift from the eastern edge of the flat and rolling plains and tablelands to the dissected western canyons and high peaks of the Rocky Mountain Cordillera. As a reflection of the interaction between atmosphere and land surface, the land cover changes from agricultural cropland, pastures, and grasslands in the east to mountain forests and shrubland basins in the west.

2. Methods

Validation of LAPS assimilations required hourly LAPS data, independent meteorological observations, meteorological-station site characteristics, and statistical analyses. LAPS validations were performed for assimilations spanning 1 September 2001-31 August 2003 over the domain of interest (Fig. 1).

a. LAPS assimilations

The Local Analysis and Prediction System (Albers 1995; Albers et al. 1996; Birkenheuer 1999; Mcginley et al. 1991), developed and operated by the NOAA's Forecast Systems Laboratory (FSL) in Boulder, Colorado, combines a wide array of observed meteorological datasets into a unified atmospheric analysis with a time interval of an hour or less. An analysis contains both spatially and temporally continuous atmospheric state variables in addition to special atmospheric and land-based fields over Colorado, Wyoming, and portions of the surrounding states (Fig. 1). The quasi-operational analyses data used in the study described herein, employs a 10-km horizontal grid (125 x 105) with 21 isobaric vertical levels and hourly temporal resolution (Liston et al. 2004b).

LAPS starts with a first guess or background field interpolated to a finer grid from coarser large-scale forecast model output (e.g., Rapid Update Cycle forecasts; Benjamin et al. 2004a; Benjamin et al. 2004b). The LAPS is a series of routines that merges observations with other nationally disseminated data and modifies the atmospheric analysis to match available observations. Different analysis methods are currently used in the routines consisting of Kalman, traditional Barnes, and variational minimization techniques, depending on the dataset (e.g., Daley 1991).

LAPS employs a wide range of observational datasets as part of its diagnoses, including 1) surface observations at specific sites every 5 minutes, 2) hourly surface aviation observations, 3) Doppler radar volume scans every 6 minutes, 4) wind and temperature Radio Acoustic Sounding System (RASS) profiles from the NOAA Demonstration Profiler Network every 60 minutes, 5) satellite visible data every 15-30 minutes, 6) multi-spectral image and sounding radiance data every 60 minutes, 7) Global Positioning System (GPS) total precipitable water

vapor determined from signal delay, and 8) automated aircraft observations. Further, quality control measures were used to assess the observations and reject those deemed unsuitable.

LAPS topography and land surface is based on USGS land use data that provides 24 land application and vegetation-type categories along with the basis for discerning water/land fraction in the domain. Soil type is derived from United Nations FAO/STATSGO data with a horizontal resolution of 30 seconds that classifies 16 soil categories including texture within two layers. The top layer extends to 30 cm below the surface and the second layer extends from that point to 90 cm under the surface.

Preparation for the comparison involved extracting LAPS data from the LAPS grid point nearest the independent meteorological stations. Additional processing was not employed for the hourly comparisons, but for daily comparisons, LAPS data were aggregated to daily maximums, minimums, and average values.

b. Independent meteorological observations

Validation of the LAPS diagnoses required comparison with meteorological data not used in the LAPS analyses. Such datasets are routinely collected by educational and agricultural observational networks and field experiment campaigns. Independent data sources utilized for validation included a total of 107 stations from the Cold Land Processes Experiment (CLPX, Cline et al. 2002), Colorado Agricultural Meteorological network (COAGMET, <http://ccc.atmos.colostate.edu/~coagmet/>), the GLOBE Program (<http://www.globe.gov/>), and the High Plains Regional Climate Center's Automatic Weather Data Network (AWDN, <http://www.hprcc.unl.edu/awdn/>).

Validation sources possessed a range of observed variables and temporal resolutions. All stations monitored air temperature, relative humidity, and precipitation. With the exception of GLOBE data, all stations also collected wind speed. Observations ranged in frequency from 10 minutes (CLPX) to daily (GLOBE); the remaining sources performed hourly measurements. Since CLPX data were observed at a finer resolution than LAPS assimilations, they were aggregated to hourly observations. Comparisons using GLOBE data involved aggregating LAPS data to a daily time-step. After the data were collected, they were quality checked (Liston et al. 2004a) and prepared for comparisons with the LAPS diagnoses.

c. Station site characteristics

1) Land cover

Spatial data were also necessary to perform the LAPS validation with respect to variation in land cover and elevation within the domain (Fig. 1). Land surface characteristics have been shown to influence local weather characteristics and diurnal fluctuations (Pielke et al. 2000; Pielke et al. 2003). We also desired to identify and assess the potential influence of land cover on the errors associated with LAPS assimilations and observed data.

A 30 m resolution National Land Cover Dataset (NLCD, Vogelmann et al. 2001) was obtained from the USGS Seamless Data Distribution System for the entire LAPS domain (Fig. 1). Because we wanted to accurately represent the predominant land-cover type associated with each station, the 30 m resolution NLCD was resampled to 1 km, station coordinates were intersected with the 1 km NLCD data in a geographic information system (GIS), and each independent observation site was attributed with a predominant land-cover class.

2) Elevation

Because the LAPS assimilations were performed at 10 km horizontal grid increments, observed differences in LAPS diagnoses and observations were considered together with the topographical representation LAPS employed versus the actual elevation of the meteorological source. Thus, station locations were intersected with the LAPS elevation to calculate the difference between LAPS and actual elevations.

d. Statistical analyses

The LAPS validation process occurred in two principal steps. In the first step, LAPS data were compared directly with observations using simple linear regressions without transformations. The direct comparisons included air temperature, relative humidity, wind speed, and precipitation.

The second step entailed the assessment of errors identified in the first step with respect to surface cover and elevation characteristics of the observation locations. To evaluate the role of land cover, one-way analysis of variance (ANOVA) was performed using the temperature, relative humidity, wind speed, and precipitation estimates of variance (r^2) as the response and land-cover class as the factor (Minitab 2000). Tukey's one-way multiple comparisons (family rate = 0.05) were employed to assess differences in r^2 among the cover types. Elevation values (observation elevation and LAPS elevation minus observation elevation) were compared against the temperature, relative humidity, wind speed, and precipitation r^2 values using simple linear regressions.

3. Results and discussion

Simple linear regressions of LAPS assimilations versus observations of temperature, relative humidity, wind speed, and precipitation illustrated the abilities of LAPS to represent the four examined meteorological characters (Fig. 2). The linear regressions performed on two years of temperature and relative humidity data from 107 and 99 stations, respectively, indicated that much of the variation in observed data is duplicated in the LAPS assimilations. The mean r^2 values associated with the temperature and relative humidity analyses are 0.96 and 0.82, respectively. The variation represented by most equations with respect to LAPS and observed wind speeds (99 stations) was intermediate overall; the mean regression r^2 value was 0.50. Lastly, the average of 96 station r^2 values for precipitation was the poorest among the compared meteorological variables (0.32).

In addition to having the highest average r^2 value, the range of temperature r^2 values was also relatively small (Fig. 2) compared with the other meteorological variables. In most cases, r^2 values of the temperature comparisons were similar among the examined stations. In contrast, wind-speed and precipitation r^2 values possessed larger ranges of r^2 values, indicating a substantial variation in agreement among the stations. Wind-speed r^2 values were particularly variable, since agreements ranged from 0.01 to 0.85.

a. Sidney, Nebraska, Case Study

While many linear regressions provided a rigorous test of how well the LAPS assimilations represented the examined meteorological conditions among a number of distinct locations, more investigation into the comparisons at specific locations is required. However, presenting 107 sets of statistics on linear regressions performed on hourly data over a period of 2

years is not practical. Instead, a station located in the high-plains grassland of western Nebraska and operated by the High Plains Regional Climate Center (2003) was randomly selected to more thoroughly assess LAPS assimilations against observations with respect to diurnal and seasonal cycles. Comparing the observations with LAPS diagnoses on an hourly timescale is easily done by coincidentally plotting the values and examining the individual linear regression plots for the stations.

1) Temperature

Temperature values were nearly identical in the LAPS assimilations compared with the independent observations associated with the Sidney, Nebraska, site (Fig. 3). In the plots, no temporal lags exist and differences between the two plots are barely discernable during the three examined months. As expected, afternoon temperatures were highest while nighttime and morning temperatures were lower. Fall, winter, and spring (Figs 3a-c) diurnal patterns and extremes in temperature are represented in both records; few LAPS data points deviate from the observed record. There are only a handful of LAPS temperature data points that stray from the lower bounds of observed temperatures in the fall (e.g., 22 Sept. 2002; Fig. 3a) and winter (e.g., 16-17 Jan. 2003; Fig. 3b) profiles.

The simple linear regression performed on the LAPS and observed records (Fig. 3d) indicated that agreement was high ($r^2 = 0.98$) and the slope of the equation approximated a 1:1 relationship. Furthermore, the cloud of compared points shows a small level of variation around the 1:1 regression line and a y-intercept close to 0, indicating that there were no clear errors with respect to temperature and few differences between LAPS and observed data.

The Sidney, Nebraska, temperature comparison possessed a slightly higher than average r^2 value (0.95) compared with the other 106 analyses performed. The Sidney, Nebraska, analysis was typical of most temperature analyses performed during the course of this validation project: LAPS assimilations were remarkably accurate in depicting hourly, daily, and seasonal temperatures. In almost all of the comparisons, LAPS and observation temperature values were closely matched.

Why was air temperature so well represented in LAPS? Air temperature is a continuous variable that varies relatively smoothly through time and space, and these changes tend to be moderate and predictable based on characteristics of atmospheric dynamics, elevation (Pielke et al. 1977) and land surface characteristics (vegetation, soil moisture, etc.; Marshall et al. 2004a; Marshall et al. 2004b). The LAPS assimilations and algorithms employed to capture the dynamics of air temperature (Kalman system) appear to be successful within the validation domain (Fig. 1).

2) Relative Humidity

Relative humidity values produced by LAPS were closely matched with concurrent observations (Fig. 4). As was the case with the temperature comparisons, temporal lags between the datasets are not apparent. September 2002, January 2003, and May 2003 (Figs. 4a-c) comparisons exhibited diurnal trends where afternoon humidity values were low while nighttime humidity levels were high. LAPS and observational data closely match overall. However, during instances of higher observed relative humidity values, similarities among the two datasets fade (Figs. 4a-c). It should be noted that some of this behavior may be attributed to increased sensor error at higher relative humidity values.

The simple linear regression for the Sidney station revealed the relationship between LAPS and observed data. The proportion of variability in the LAPS data accounted for by the observations was 92%, slope was 0.90, the y-intercept was 8.6, and moderate scatter of data points existed along the regression line (Fig. 4d). Like the temperature comparison, the relative humidity validation indicated that much of the variance between LAPS and observed data was explained in the linear model ($r^2 = 0.92$). The lower slope and a y-intercept > 0 in the equation indicated that at higher observed relative humidity values, LAPS data have a slightly lower relative humidity than the observed value. In contrast, at lower observed humidity levels, LAPS relative humidity values are slightly higher than the observed data. Lastly, the scatter of points around the regression line indicated that LAPS and observed data agreement was more probable at lower relative humidity values, and there is a higher chance of mismatch at higher relative humidity values.

The Sidney comparison r^2 value (0.92) is somewhat higher than the average r^2 value (0.82) associated with the remaining 98 comparisons of relative humidity. However, the general trends identified with slope, y-intercepts, and scatter were common to the vast majority of the other comparisons. In general, LAPS and observed data were closely matched with respect to relative humidity values.

Relative humidity, in contrast to temperature, is less spatially continuous and changes dramatically at distances < 30 km (Camargo et al. 1999; Hubbard 1994). Despite, this variability in relative humidity, the relationships between LAPS and observations were strong. Moreover, it is likely that this high level of agreement is related to the successful representation of temperature.

3) Wind Speed

LAPS and observed wind speed values are more divergent than demonstrated with temperature and relative humidity comparisons (Fig. 5). General trends in observed wind speed are characterized in LAPS data, and no obvious temporal mismatches are present (Figs. 5a-c). Overall, the LAPS data are more extreme than the observations during the examined months (Figs. 5a-c).

The simple linear regression performed on the Sidney LAPS and observation comparison revealed an intermediate variance agreement, a slope >1 , a y-intercept close to 1, and variable scatter along the regression line (Fig. 5d). The r^2 value for the wind-speed regression indicated that 71 percent of the variation in the LAPS assimilation exists in the observed data. The slope value of 1.07 revealed that LAPS slightly overestimates wind speeds in this location compared with observations. The y-intercept of 0.06 shows that LAPS also barely overestimates wind speeds at low observed wind speeds. Scatter around the regression line is relatively uniform up to 10 m s^{-1} ; it tapers at speeds above that due to the lower frequency of higher wind speeds in this location.

The Sidney wind-speed comparison focused on a case that was close to the 90th percentile of all cases (Fig. 2) in terms of its r^2 value. More importantly, the wind-speed comparisons were the most variable with respect to the relationship between LAPS and observed data; the average r^2 for the remaining 98 wind speed comparisons was a substantially lower 0.50 (Fig. 2). The other examined cases also possessed inconsistent slopes (ranging from 0.27 to 1.26) and y-intercepts (from 0.25-3.0).

The erratic relationship between LAPS and the observed wind-speed data is indicative of the spatial variability associated with wind speed (Arya 2001; Hubbard 1994). While winds are

relatively consistent above the well-mixed daytime boundary layer, they interact with the surface and surface features (e.g., topography and vegetation) to produce spatially variable wind speeds. The potential influence of surface features on the relationship between LAPS and observed wind speeds are explored below (see *Station Site Characteristics*).

4) Precipitation

The precipitation comparison showed the highest level of disagreement among the four compared meteorological variables (Fig. 6). In most cases, the LAPS data showed evidence of precipitation where none was observed during the same period (Figs. 6a-c). When precipitation was observed, there usually was precipitation in the concurrent LAPS data. It should be noted that the entire January dataset (Fig. 6b; High Plains Regional Climate Center 2003) in the Sidney observations were flagged because they lacked confidence in the precipitation estimate. In fact, no precipitation was recorded at Sidney during the month of January, indicating that their lack of confidence was probably well-founded.

The simple linear regression equation for the Sidney LAPS and observed precipitation comparison revealed the explained variation, slope, y-intercept, and scatter along the regression line (Fig. 6d). The r^2 value from the regression indicated that 24% of the variance between the two datasets was explained by the equation. The slope was greater than 1 and the y-intercept was slightly greater than 0, indicating that LAPS assimilations generally overstated precipitation, especially at higher observed precipitation levels. There is abundant scatter along the regression line at lower observed ($< 5 \text{ mm hour}^{-1}$) precipitation levels (Fig. 6d).

The disparity between LAPS and observed precipitation is likely a function of observational error, LAPS calculation of precipitation from radar and satellite data, and scaling

differences. Precipitation measurements are some of the more difficult meteorological measurements to make accurately (Ahrens 2003; Shih 1982), especially when snow is accompanied by wind (Yang et al. 1998), which is a common winter occurrence in the LAPS domain (Fig. 1). LAPS also calculates precipitation with the aid of radar and satellite observations that can over/underestimate precipitation (Brandes et al. 1999; Klazura et al. 1999; Legates 2000). Lastly, it is important to remember that the LAPS system studied here operates on a scale of 10 horizontal kilometers while the compared observations are point measurements located within that 10 km. Precipitation amounts within that 10 by 10 km area may not be reflected by a point within that area, especially when precipitation is convective in origin (Pielke 2001).

b. Station site characteristics

1) Land Cover

Two site characteristics were assessed with respect to the r^2 values produced by the simple linear regressions: land cover and elevation. The 107 stations used for validation of LAPS assimilations were located in 13 different 1-km-aggregated National Land Cover classes (with quantity in parentheses): water (1), residential (2), urban (4), bare (1), deciduous forest (1), evergreen forest (2), shrubland (6), urban grassland (1), grassland (37), pasture/hay (15), small grain (14), row cropland (22), and alpine (1). According to the unbalanced one-way ANOVAs, r^2 values were significantly different among the land-cover classes for temperature, relative humidity, and wind-speed comparisons (Fig. 7, Table 1). The r^2 values among precipitation comparisons and cover classes were not significantly different.

How were the land cover types different with respect to accuracies among LAPS and observed data? Mean r^2 values of the temperature comparisons were all high with the exception of the residential cover class, which was identified as significantly lower (0.05 family error in a Tukey pairwise comparison) than the pasture/hay, grassland, row crop, small grain, and shrubland classes (Fig. 7a). While the relative humidity r^2 values were significantly different in the ANOVA (Table 1), Tukey pairwise comparisons using 0.05 and 0.10 family error rates failed to identify classes different from each other (Fig. 7b). With regard to wind speeds (Fig. 7c), evergreen r^2 values were significantly lower (0.05 family error) than grassland, small grains, row cropland, and urban classes. In addition, shrubland wind speed r^2 values were significantly lower than those associated with row crops.

It is important to note the disparity among land-cover class memberships that were used to delineate these differences among land-cover types and LAPS-observation discrepancies. Stations associated with water, residential, urban, bare, deciduous forest, evergreen forest, urban grassland, and alpine classes possessed less than 3 members; results related to these classes should be treated with appropriate skepticism and caution. It is not a matter of being attributed a false significance with respect to the r^2 differences; the Tukey test at a 0.05 family error rate is a conservative test (Neter et al. 1996). Rather, the error lies with classes that have a low sample size where stations having a high leverage were used to calculate the mean. For example, the r^2 values associated with the temperature comparisons of the residential class were 0.97 and 0.64 (Fig. 7a). The one station with the poorer 0.64 value made the residential class significantly different from the pasture/hay, grassland, row crop, small grain, and shrubland classes.

With the lack of replications in mind, the most concrete land cover and accuracy relationship is associated with shrubland r^2 being lower than row crop r^2 values for the wind-

speed comparisons. Reasons for the disparity may be associated with weather differences among the land cover types or some other combination of potential characteristics (e.g., surface roughness).

2) Elevation

No discernable relationships existed for elevation and r^2 values associated with temperature, relative humidity, and precipitation (data not shown). However, station elevation possessed a significant linear relationship with r^2 values produced by the wind-speed comparisons (Fig. 8). As the elevation of the observation location increased, the r^2 values exhibited a marked decrease ($r^2 = 0.61$; $p < 0.0001$). This 61% explanation in variance due to elevation indicates that topography, forest cover, or some combination of these factors contributes to the higher rate of disparities present between LAPS and observed wind speeds. Differences in r^2 values due to disparities between the 10 km horizontal grid increment LAPS DEM and the observation-station elevation were not significant with any of the four meteorological factors evaluated. Thus, it is reasonable to assume that the topographical resolution of LAPS was not the source of any disparities between LAPS data and observations.

4. Conclusions

LAPS assimilations were remarkably accurate in depicting temperature and relative humidity values temporally and spatially. Observed diurnal changes in temperature and relative humidity were duplicated by LAPS regardless of land-cover type and elevation associated with the 107 stations employed in this project. Spatial variation in temperature and relative humidity

was also successfully represented by LAPS. For example, mountain and grasslands, each with their distinctive weather characteristics, were well represented by LAPS.

Wind speed and precipitation relationships between LAPS and observed datasets were more variable. Wind speeds were reasonably represented by LAPS assimilations and accuracy was much higher for lower elevations. The main reason for the disparity in precipitation values remains unknown but likely involves some combination of LAPS and observational errors and scaling issues.

The LAPS system is a valuable and reliable choice for applications that require high temporal resolution and spatially distributed meteorological data. LAPS is a realistic data assimilation system; it extends the capabilities of its users to areas where few meteorological data sources exist or where those sources are often unreliable. Additionally, LAPS improvements underway (e.g., smaller horizontal resolution) are likely to extend the capabilities of this system and potentially remedy disparities among precipitation estimates and observations.

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REFERENCES

- Ahrens, C. D., 2003: *Meteorology Today: An Introduction to Weather, Climate, and the Environment*. 7 ed. Thomson/Brooks/Cole, 624 pp.
- Albers, S. C., 1995: The LAPS wind analysis. *Wea. Forecasting*, **10**, 342-352.
- Albers, S. C., J. A. McGinley, D. L. Birkenheuer, and J. R. Smart, 1996: The local analysis and prediction system (LAPS): analyses of clouds, precipitation, and temperature. *Wea. Forecasting*, **11**, 273-287.
- Arya, S. P., 2001: *Introduction to Micrometeorology*. 2nd ed. Academic Press, 420 pp.
- Benjamin, S. G., G. A. Grell, J. M. Brown, T. G. Smirnova, and R. Bleck, 2004a: Mesoscale weather prediction with the RUC hybrid isentropic-terrain-following coordinate model. *Mon. Wea. Rev.*, **132**, 473-494.
- Benjamin, S. G., D. Devenyi, S. S. Weygandt, K. J. Brundage, J. M. Brown, G. A. Grell, D. Kim, B. E. Schwartz, T. G. Smirnova, T. L. Smith, and G. S. Manikin, 2004b: An hourly assimilation-forecast cycle: the RUC. *Mon. Wea. Rev.*, **132**, 495-518.
- Birkenheuer, D., 1999: The effect of using digital satellite imagery in the LAPS moisture analysis. *Wea. Forecasting*, **14**, 782-788.
- Brandes, E. A., J. Vivekanandan, and J. W. Wilson, 1999: A comparison of radar reflectivity estimates of rainfall from collocated radars. *J. Atmos. Oceanic Technol.*, **16**, 1264-1272.
- Camargo, M. B. P. and K. G. Hubbard, 1999: Spatial and temporal variability of daily weather variables in sub-humid and semi-arid areas of the United States high plains. *Agric. For. Meteorol.*, **93**, 141-148.
- Cline, D., K. Elder, B. Davis, J. Hardy, G. E. Liston, D. Imel, S. H. Yueh, A. J. Gasiewski, G. Koh, R. L. Armstrong, and M. Parsons, 2002: Overview of the NASA cold land

- processes field experiment (CLPX-2002). *Microwave Remote Sensing of the Atmosphere and Environment III*, Hangzhou, China, The Society of Photo-Optical Instrumentation Engineers, 361-372.
- Daley, R., 1991: *Atmospheric Data Analysis*. Cambridge Atmospheric and Space Science Series 2. Cambridge University Press, 457 pp.
- High Plains Regional Climate Center, cited 2003: Automatic Weather Data Network. [Available online from <http://www.hprcc.unl.edu/awdn/home.html>.]
- Hubbard, K. G., 1994: Spatial variability of daily weather variables in the high plains of the USA. *Agric. For. Meteorol.*, **68**, 29-41.
- Jasper, K., J. Gurtz, and L. Herbert, 2002: Advanced flood forecasting in alpine watersheds by coupling meteorological observations and forecasts with a distributed hydrological model. *J. Hydrol.*, **267**, 40-52.
- Klazura, G. E., J. M. Thomale, D. S. Kelly, and P. Jendrowski, 1999: A comparison of NEXRAD WSR-88D radar estimates of rain accumulation with gauge measurements for high- and low-reflectivity horizontal gradient precipitation events. *J. Atmos. Oceanic Technol.*, **16**, 1842-1850.
- Legates, D. R., 2000: Real-time calibration of radar precipitation estimates. *Prof. Geogr.*, **52**, 235-246.
- Liston, G. E. and M. Sturm, 1998: A snow transport model for complex terrain. *J. Glaciol.*, **44**, 498-516.
- , 2002: Winter precipitation patterns in arctic Alaska determined from a blowing-snow model and snow-depth observations. *J. Hydrometeorol.*, **3**, 646-659.

- Liston, G. E. and K. Elder, 2004a: A Meteorological distribution system for high resolution terrestrial modeling (MicroMet). *J. Hydrometeorol.*, In review.
- Liston, G. E., D. L. Birkenheuer, D. Cline, and K. Elder, 2004b: Atmospheric analyses data sets for the Cold Land Processes Experiment (CLPX). *J. Hydrometeorol.*, In review.
- Marshall, C. H., R. A. Pielke, and L. T. Steyaert, 2004a: Has the conversion of natural wetlands to agricultural land increased the incidence and severity of damaging freezes in south Florida? *Mon. Wea. Rev.*, In Press.
- Marshall, C. H., R. A. Pielke, L. T. Steyaert, and D. A. Willard, 2004b: The impact of anthropogenic land-cover change on the Florida peninsula sea breezes and warm season sensible weather. *Mon. Wea. Rev.*, **132**, 28-52.
- Mcginley, J. A., S. C. Albers, and P. A. Stamus, 1991: Validation of a composite convective index as defined by a real-time local analysis system. *Wea. Forecasting*, **6**, 337-356.
- Minitab Inc., 2000: Minitab Statistical Software Version 13.32. Minitab, Inc.
- Neter, J., M. H. Kutner, C. J. Nachtsheim, and W. Wasserman, 1996: *Applied linear statistical models*. 4th ed. Irwin, 1408 pp.
- Parton, W. J., M. Hartman, D. Ojima, and D. Schimel, 1998: DAYCENT and its land surface submodel: description and testing. *Global Planet. Change*, **19**, 35-48.
- Peet, R. K., 2000: Forests and meadows of the Rocky Mountains. *North American terrestrial vegetation*. 2nd ed. M. G. Barbour and W. D. Billings, Eds., Cambridge University Press, 75-121.
- Pielke, R. A., 2001: Influence of the spatial distribution of vegetation and soils on the prediction of cumulus convective rainfall. *Rev. Geophys.*, **39**, 151-177.

- Pielke, R. A. and P. Mehring, 1977: Use of mesoscale climatology in mountainous terrain to improve spatial representation of mean monthly temperatures. *Mon. Wea. Rev.*, **105**, 108-112.
- Pielke, R. A., T. Stohlgren, W. Parton, N. Doesken, J. Moeny, L. Schell, and K. Redmond, 2000: Spatial representativeness of temperature measurements from a single site. *Bull. Amer. Meteor. Soc.*, **81**, 826-830.
- Pielke, R. A., G. Marland, R. A. Betts, T. N. Chase, J. L. Eastman, J. O. Niles, D. Niyogi, and S. W. Running, 2003: The influence of land-use change and landscape dynamics on the climate system: Relevance to climate-change policy beyond the radiative effect of greenhouse gases. *Capturing Carbon and Conserving Biodiversity: The Market Approach*, I. R. Swingland, Ed., Earthscan Publications Ltd., 157-172.
- Pielke, R. A., T. Stohlgren, L. Schell, W. Parton, N. Doesken, K. Redmond, J. Moeny, T. McKee, and T. G. F. Kittel, 2002: Problems in evaluating regional and local trends in temperature: an example from eastern Colorado, USA. *Int. J. Climatol.*, **22**, 421-434.
- Running, S. W. and J. C. Coughlan, 1988: A general-model of forest ecosystem processes for regional applications .1. Hydrologic balance, canopy gas-exchange and primary production processes. *Ecol. Model.*, **42**, 125-154.
- Scuderi, L. A., C. B. Schaaf, K. U. Orth, and L. E. Band, 1993: Alpine treeline growth variability: simulation using an ecosystem process model. *Arc. Alp. Res.*, **25**, 175-182.
- Shih, S. F., 1982: Rainfall variation analysis and optimization of gauging systems. *Water Resour. Res.*, **18**, 1269-1277.
- Sims, P. L. and P. G. Risser, 2000: Grasslands. *North American Terrestrial Vegetation*. 2nd ed. M. G. Barbour and W. D. Billings, Eds., Cambridge University Press, 323-356.

Vogelmann, J. E., S. M. Howard, L. M. Yang, C. R. Larson, B. K. Wylie, and N. Van Driel,

2001: Completion of the 1990s National Land Cover Data set for the conterminous

United States from Landsat Thematic Mapper data and Ancillary data sources.

Photogramm. Eng. Remote Sensing, **67**, 650-652.

Westrick, K. J., P. Storck, and C. F. Mass, 2002: Description and evaluation of a

hydrometeorological forecast system for mountainous watersheds. *Wea. Forecasting*, **17**,

250-262.

Yang, D. Q., B. E. Goodison, J. R. Metcalfe, V. S. Golubev, R. Bates, T. Pangburn, and C. L.

Hanson, 1998: Accuracy of NWS 8" standard nonrecording precipitation gauge: Results

and application of WMO intercomparison. *J. Atmos. Oceanic Technol.*, **15**, 54-68.

FIGURE CAPTIONS

FIG. 1. The LAPS domain, portrayed in this MODIS enhanced vegetation index (EVI) image, envelops Colorado, Wyoming, and portions of surrounding states. Data used for validation include the Cold Land Processes Experiment (CLPX), Colorado Agricultural Meteorological Network (COAGMET), GLOBE, and the High Plains Regional Climate Center's Automatic Weather Data Network (AWDN).

FIG. 2. The variability in the LAPS assimilations accounted for in the observations is represented by the r^2 value produced by simple linear regression equations. The box plots display the mean (dashed line); median (solid line); and 10th, 25th, 75th and 90th percentiles of the r^2 values. Temperature and relative humidity values possess the highest agreement among LAPS diagnoses and observations, while wind speed and precipitation agreements are lower and more variable.

FIG. 3. Sidney, Nebraska LAPS air temperature assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c). A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

FIG. 4. Sidney, Nebraska LAPS relative humidity assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c). A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

FIG. 5. Sidney, Nebraska LAPS wind speed assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c). A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

FIG. 6. Sidney, Nebraska LAPS precipitation assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c). A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

FIG. 7. The level of agreement (r^2 value) varied significantly (Table 1) with National Land Cover Data classes for temperature (a), relative humidity (b), and wind speed (c). No significant relationships existed between precipitation agreements and land cover (d). The box plots display the median (solid line); and 10th, 25th, 75th and 90th percentiles of the r^2 values.

FIG. 8. Wind speed comparison r^2 values decrease with elevation. The decrease with elevation may be related to local terrain influence, LAPS wind profile calculations, or some combination of these factors.

TABLE 1. One-way analysis of variance (ANOVA)
results for effects of land cover on regression agreement (r^2).

Analysis	d.f.	Sum of Squares	Mean Square	F-Statistic	p value
Air Temperature					
cover class	12	0.07	0.01	2.33	0.01
error	94	0.24	0.00		
Relative Humidity					
cover class	11	0.30	0.03	2.56	0.01
error	87	0.94	0.01		
Wind Speed					
cover class	11	1.36	0.12	3.92	0.0001
error	87	2.74	0.03		
Precipitation					
cover class	9	0.40	0.04	1.11	0.36
error	86	3.47	0.04		

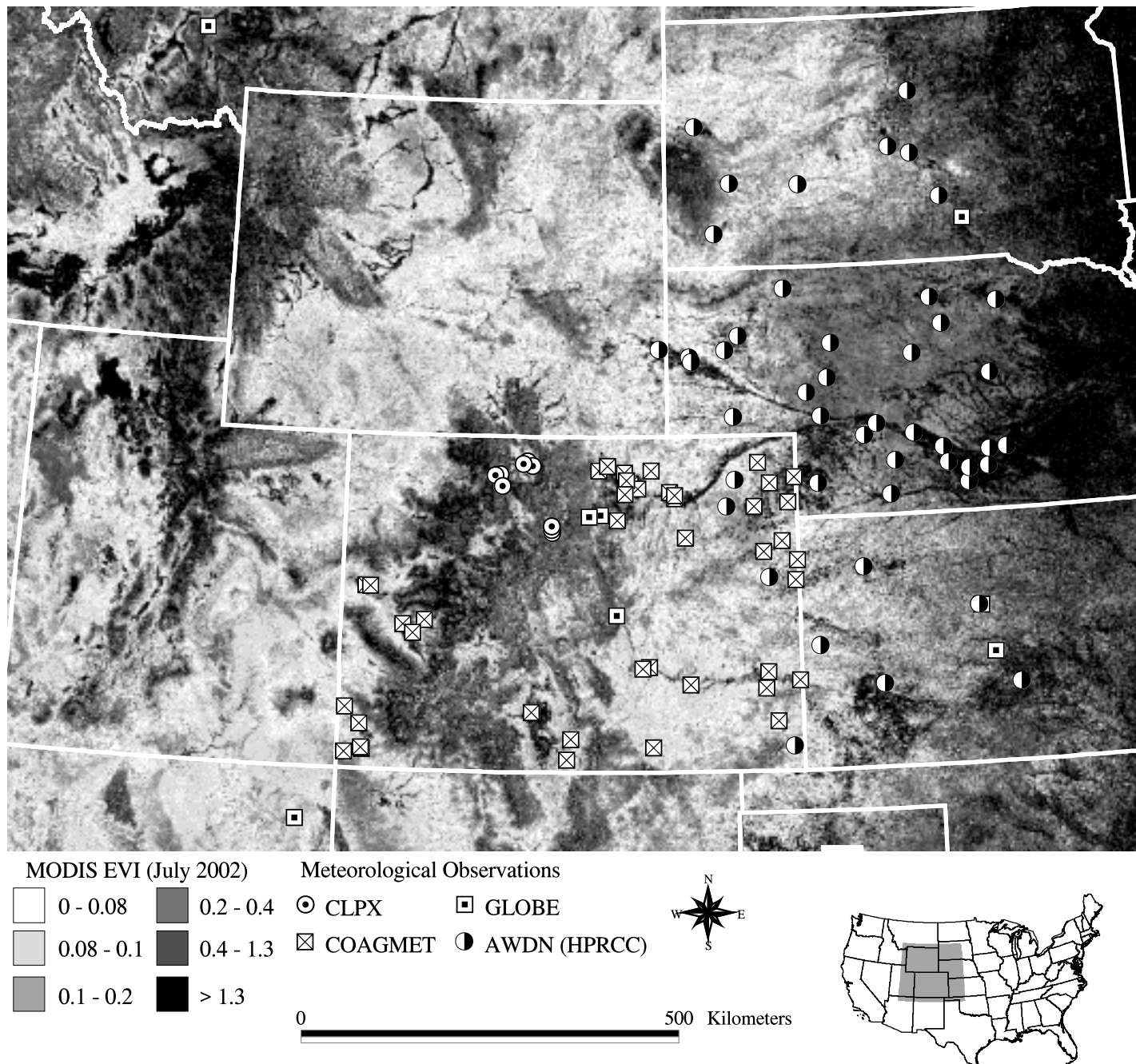


FIG. 1. The LAPS domain, portrayed in this MODIS enhanced vegetation index (EVI) image, envelops Colorado, Wyoming, and portions of surrounding states. Data used for validation include the Cold Land Processes Experiment (CLPX), Colorado Agricultural Meteorological Network (COAGMET), GLOBE, and the High Plains Regional Climate Center's Automatic Weather Data Network (AWDN).

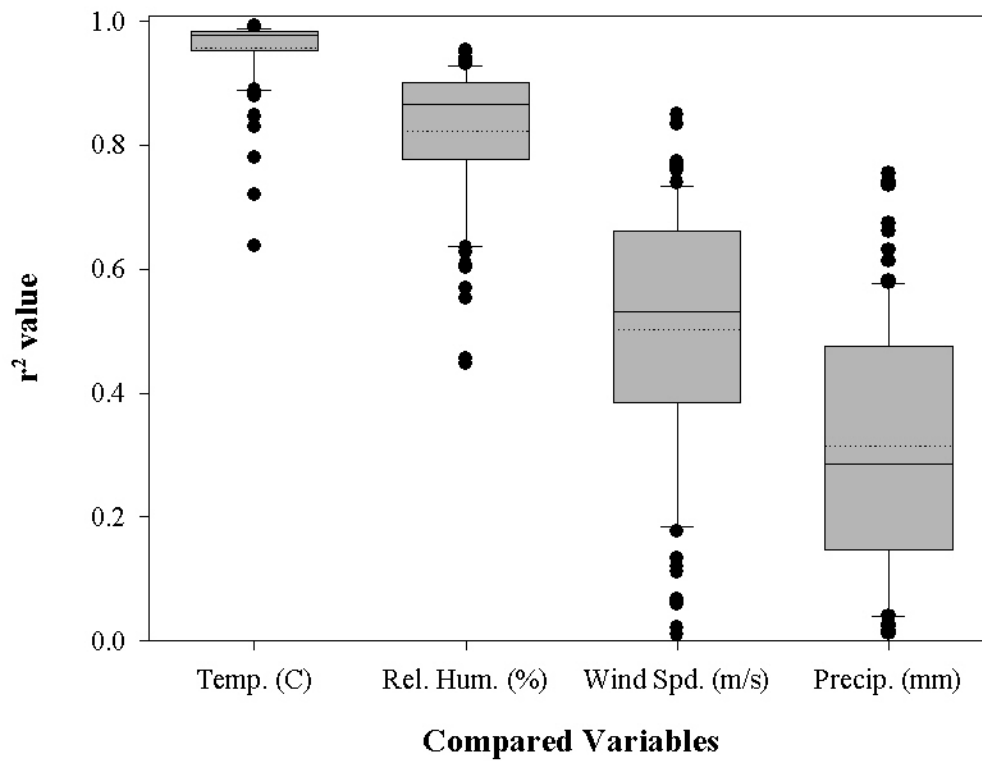


FIG. 2. The variability in the LAPS assimilations accounted for in the observations is represented by the r^2 value produced by simple linear regression equations. The box plots display the mean (dashed line); median (solid line); and 10th, 25th, 75th and 90th percentiles of the r^2 values. Temperature and relative humidity values possess the highest agreement among LAPS diagnoses and observations, while wind speed and precipitation agreements are lower and more variable.

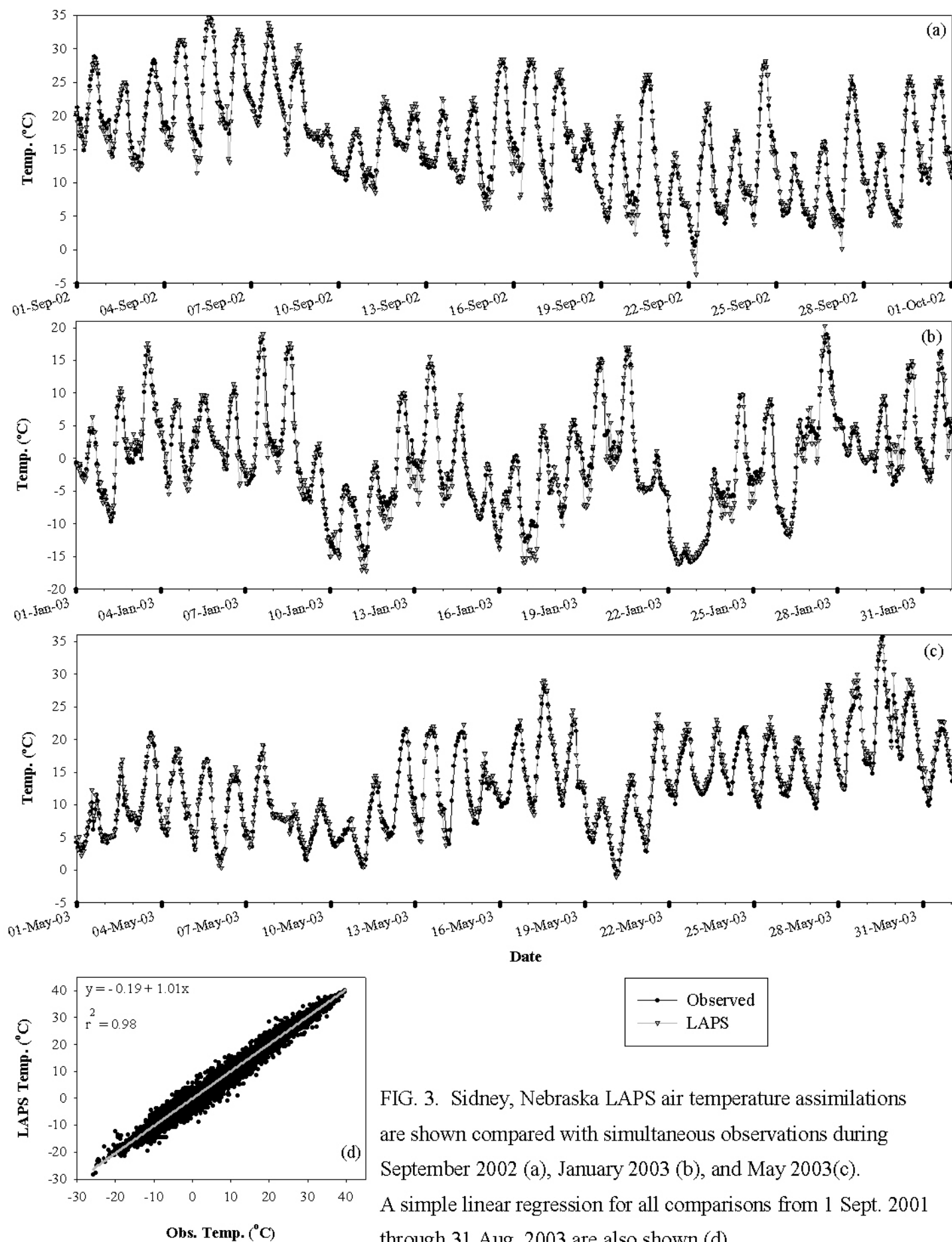


FIG. 3. Sidney, Nebraska LAPS air temperature assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003(c).

A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

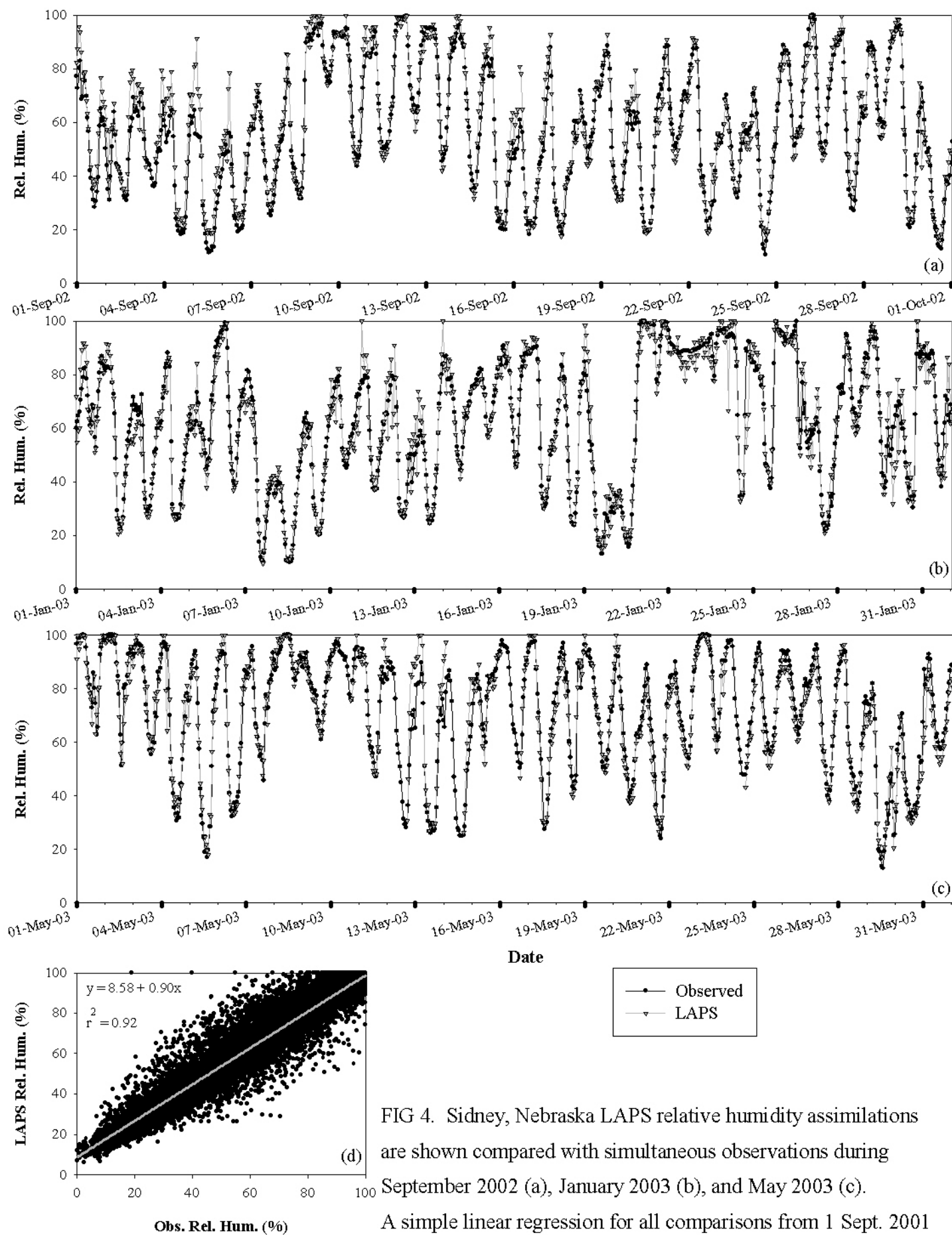


FIG 4. Sidney, Nebraska LAPS relative humidity assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c). A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

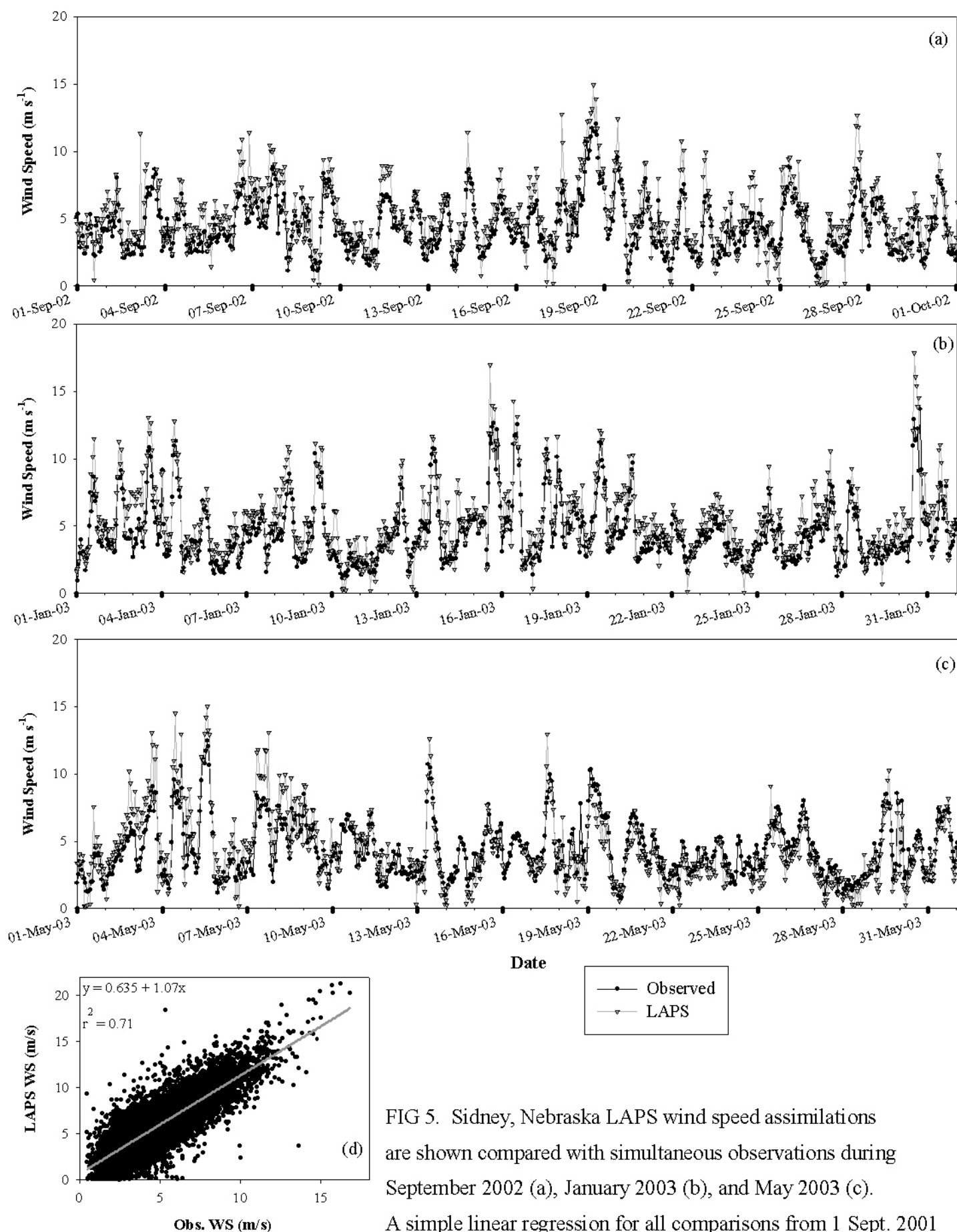


FIG 5. Sidney, Nebraska LAPS wind speed assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c).

A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

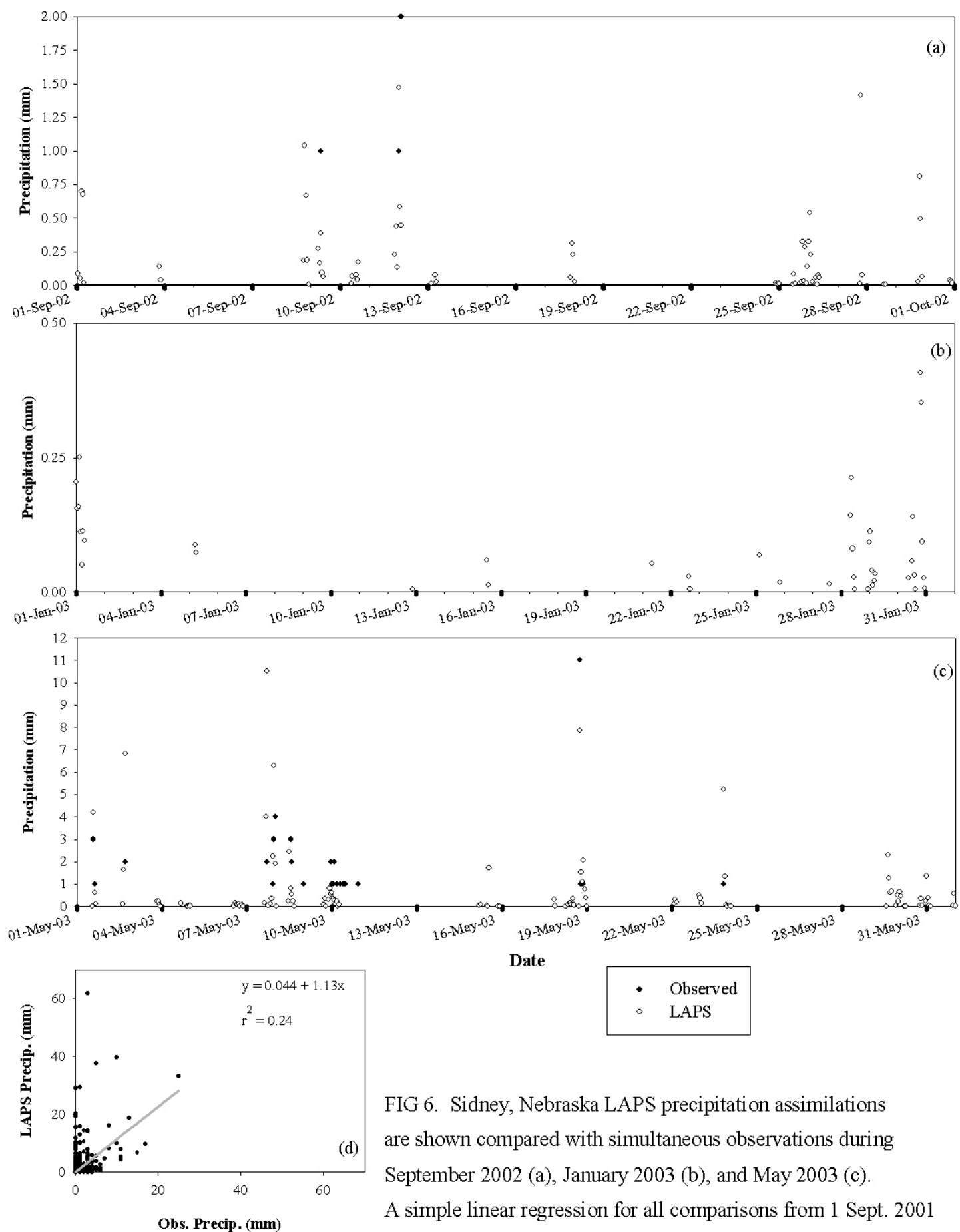


FIG 6. Sidney, Nebraska LAPS precipitation assimilations are shown compared with simultaneous observations during September 2002 (a), January 2003 (b), and May 2003 (c).

A simple linear regression for all comparisons from 1 Sept. 2001 through 31 Aug. 2003 are also shown (d).

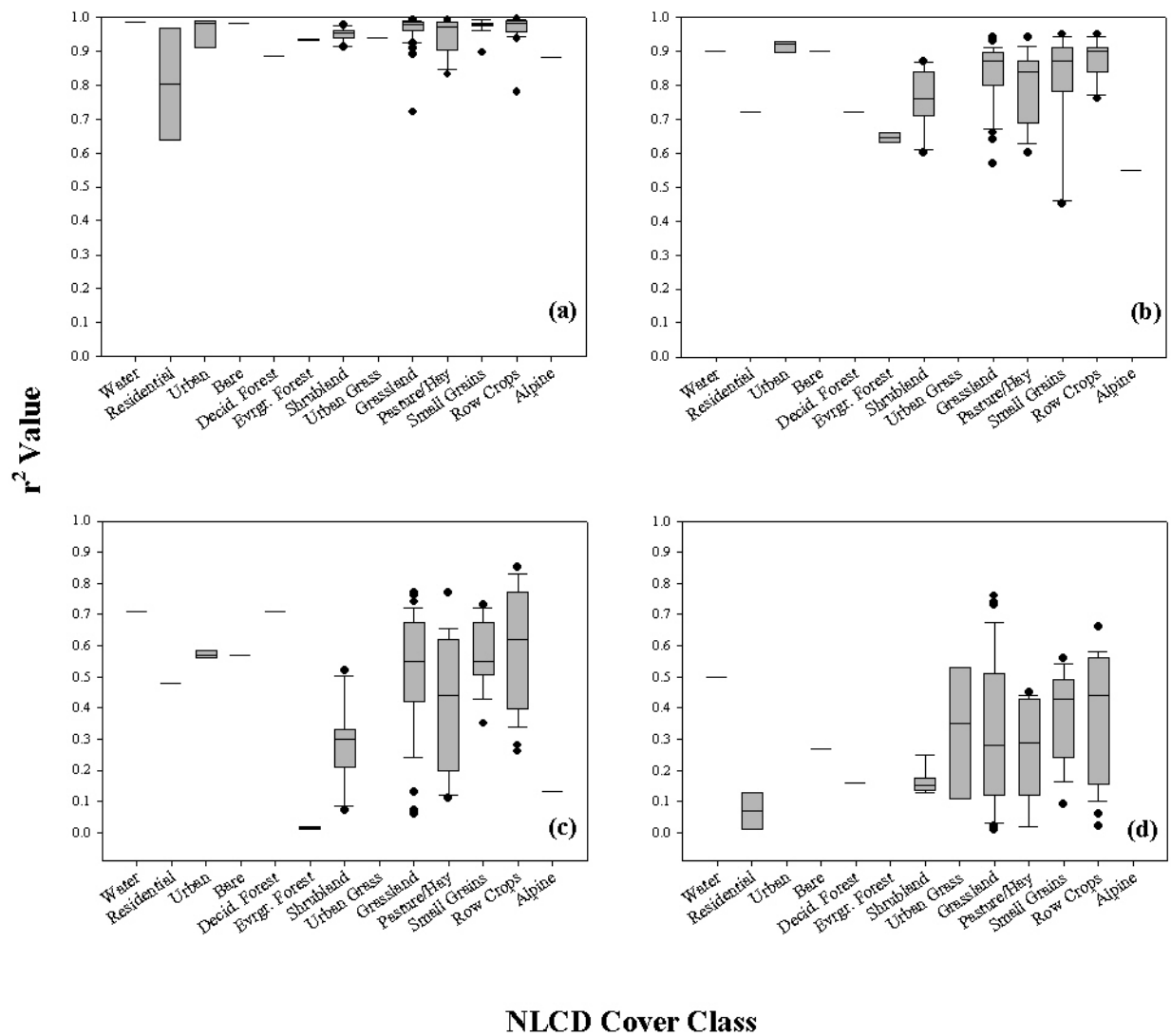


FIG. 7. The level of agreement (r^2 value) varied significantly (Table 1) with National Land Cover Data classes for temperature (a), relative humidity (b), and wind speed (c). No significant relationships existed between precipitation agreements and land cover (d). The box plots display the median (solid line); and 10th, 25th, 75th and 90th percentiles of the r^2 values.

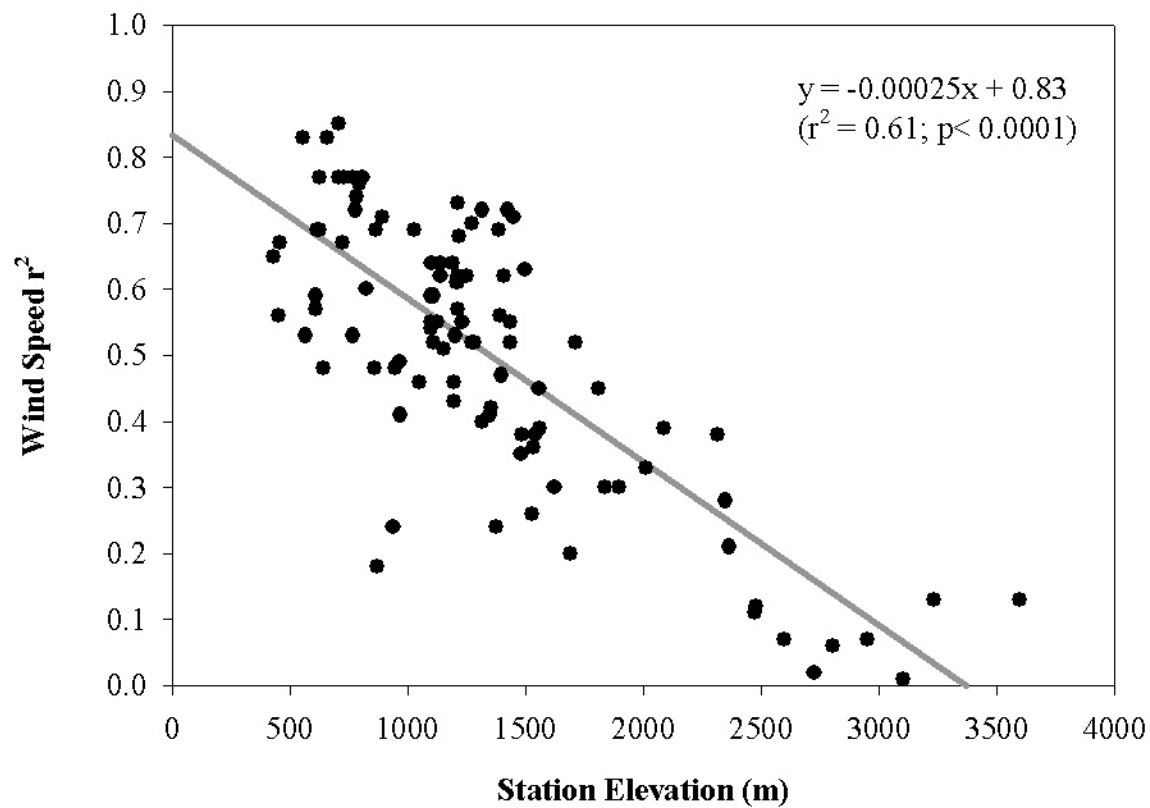


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